LCA Methodology

Application of Uncertainty and Variability in LCA

Part I: A General Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment (*Int. J. LCA 5/1998)*
Part II: Dealing with Parameter Uncertainty and Uncertainty due to Choices in Life Cycle Assessment (*Int. J. LCA 6/1998)*

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Part I: A General Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment

Abstract

As yet, the application of an uncertainty and variability analysis is not common practice in LCAs. A proper analysis will be facilitated when it is clear which types of uncertainties and variabilities exist in LCAs and which tools are available to deal with them. Therefore, a framework is developed to classify types of uncertainty and variability in LCAs. Uncertainty is divided in (1) parameter uncertainty, (2) model uncertainty, and (3) uncertainty due to choices, while variability covers (4) spatial variability, (5) temporal variability, and (6) variability between objects and sources. A tool to deal with parameter uncertainty and variability between objects and sources in both the inventory and the impact assessment is probabilistic simulation. Uncertainty due to choices can be dealt with in a scenario analysis or reduced by standardisation and peer review. The feasibility of dealing with temporal and spatial variability is limited, implying model uncertainty in LCAs. Other model uncertainties can be reduced partly by more sophisticated modelling, such as the use of non-linear inventory models in the inventory and multi media models in the characterisation phase.

Keywords: Framework, parameter uncertainty, LCA; LCA, parameter uncertainty; Life Cycle Assessment (LCA), parameter uncertainty; model uncertainty, LCA; parameter uncertainty, LCA; uncertainty, LCA; uncertainty importance analysis; variability, parameter uncertainty, LCA

1 Introduction

Uncertainty and variability are often mentioned as factors complicating the interpretation of outcomes of LCAs. Variability is understood here as stemming from inherent variations in the real world, while uncertainty comes from inaccurate measurements, lack of data, model assumptions, etc. that are used to "convert" the real world into LCA outcomes. The implementation of an uncertainty and variability analysis in LCAs may be helpful for decision makers in judging the significance of the differences in product comparisons, options for product improvements or the assignment of ecolabels.

Although the importance of dealing with uncertainty and variability is broadly accepted, a proper framework to distinguish types of uncertainty and variability in LCAs is lacking. Therefore, a classification of uncertainty and variability in LCAs seems useful. This is all the more so because different types of uncertainty and variability need to be made operational or reduced in different ways. Several authors have proposed classifications for uncertainty and variability (Morgan & Henrion, 1990; Funtowitz & Ravetz, 1990; US-EPA, 1997). This paper presents a general framework to address uncertainty and variability in LCA and builds on these classifications. The following types of uncertainty and variability are distinguished and elaborated in the sections below: (1) parameter uncertainty; (2) model uncertainty; (3) uncertainty due to choices; (4) spatial variability; (5) temporal variability and (6) variability between objects/sources (→ *Fig. 1*). Moreover, techniques and methods to deal with these types of uncertainty and variability are discussed.

2 Parameter Uncertainty

A large amount of data is usually needed in the inventory analysis and in the models which calculate characterisation and weighting factors in the impact assessment. Uncertainty of these parameters also causes uncertainty in the outcome

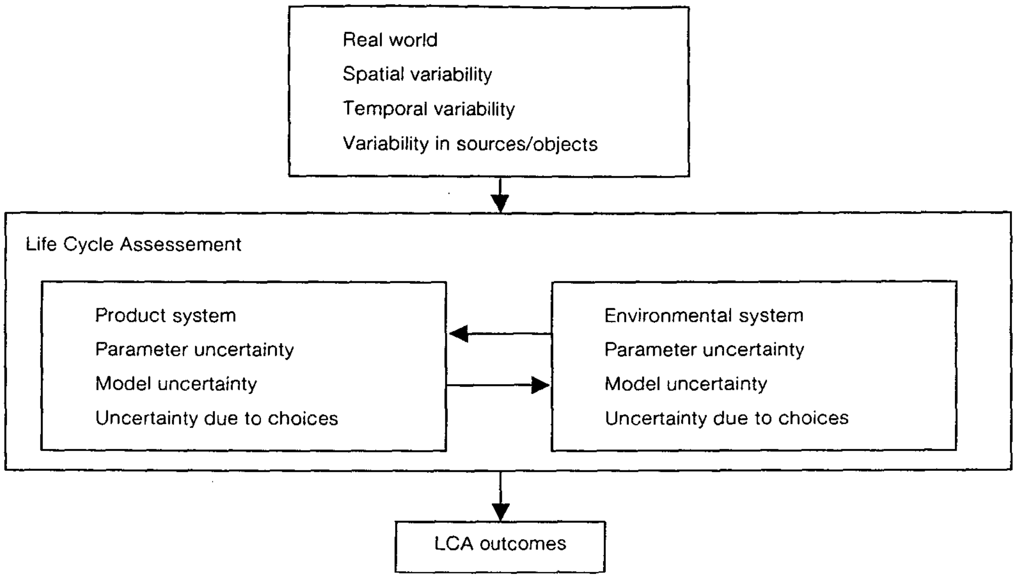

Fig. 1: Transferring the real world in LCA outcomes

of an LCA. Empirical inaccuracy (imprecise measurements), unrepresentativity (incomplete or outdated measurements) and lack of data (no measurements) are common sources of parameter uncertainty. WEIDEMA & WESNÆS (1996) describe a comprehensive procedure for estimating the combined inaccuracy and unrepresentativity of inventory data both qualitatively and quantitatively. Although this procedure may substantially improve the credibility of the outcomes of LCAs, uncertainty analysis is generally complicated by a lack of knowledge of uncertainty distributions and correlations between parameters. A substitute for lack of knowledge is the use of expert judgement to estimate uncertainty ranges of inputs in and outputs of industrial processes. In addition, a description in databases of uncertainty ranges of environmental interventions per unit process will substantially improve the feasibility of performing a standard uncertainty analysis in LCAs. A first step in this respect is the development of a common database format, in which uncertainty ranges for average life cycle inventory data should be listed (SINGHOFEN et al., 1996). However, lack of knowledge about specific processes, material use and emissions related to a product system is not compensated by assessing inaccuracy and unreliability. Additional data research and standard estimation techniques may provide useful information for filling in these data gaps (BRETZ & FRANKHOUSER, 1996).

Various methods have been proposed to make uncertainty operational in LCA outcomes due to parameter uncertainty: HOFFMAN et al. (1995) and HEIJUNGS (1996) promoted the use of analytical uncertainty propagation methods; CHEVALIER & LE TÉNO (1996) performed calculations with intervals; BECCALI et al. (1997) applied fuzzy logic computations, which is an extension of the interval concept; PETERSEN (1997) developed a method, based on Bayesian statistics, which makes it possible to treat subjective uncertainty estimates with the usual statistical calculation rules; and KENNEDY et al. (1996) used stochastic modelling, describing parameters as uncertainty distributions. Stochastic modelling, which can be performed by Monte Carlo or Latin Hypercube simulation, seems to be an especially promising technique for making uncertainty in model output operational. An advantage in relation to the other methods mentioning is that, dependent on the available information, various parameter distributions, such as uniform, triangular, normal, or lognormal distributions, can be used in the model. Furthermore, if correlations between parameters can be estimated, it is technically easy to deal with these correlations in the simulations.

To perform Monte Carlo simulation, parameters have to be specified as uncertainty distributions. The method varies all the parameters at random, but the variation is restricted by the given uncertainty distribution for each parameter. The randomly selected values from all the parameter uncertainty distributions are inserted in the output-equation. Repeated calculations produce a distribution of the predicted output values, reflecting the combined parameter uncertainties. Latin Hypercube simulation works in the same way with one exception. This method segments the uncertainty distribution of a parameter into a number of non-overlapping intervals, each having equal probability. In addition, from each interval, a value is selected at random according to the probability distribution within the interval, leading to generally more precise random samples than Monte Carlo simulation

Probabilistic uncertainty analysis is useful in making the influence of parameter uncertainty on the uncertainty of the model outcomes operational. For the reduction of parameter uncertainty, however, more reliable data must be provided by additional literature research, expert judgement or measurements. Parameters which cause the largest spread in

the model outcome should have be given priority. The contribution of the separate parameters to the total uncertainty may be estimated through the use of statistical correlation and regression techniques (JANSSEN *et al.*, 1990). Besides the possibility to perform probabilistic simulation in spreadsheets, probabilistic simulation programs, such as Crystal Ball® (DECISIONEERING, 1996), provide correlation techniques to perform an uncertainty importance analysis.

3 Model Uncertainty

Some aspects cannot be modelled within the present LCA structure. For instance, spatial and temporal characteristics are lost by the aggregation of emissions in the inventory analysis. Furthermore, in the impact assessment it is assumed that ecological processes respond in a linear manner to environmental interventions and that thresholds of interventions are disregarded (OWENS, 1996). In addition, the derivation of characterisation factors causes model uncertainty. Characterisation factors are computed with the help of simplified environmental models which also suffer from model uncertainties. For instance, the fate of substances and the sensitivity of the receiving environment are not taken into account in the computation of acidification and eutrophication factors (NICHOLS et al., 1996). With the help of multi media modelling, fate of substances and the sensitivity of the environment could be taken into account in the computation of acidification and eutrophication factors (WEGENER SLEESWIJK & HEIJUNGS, 1996; POTTING et al., 1997), reducing model uncertainty in the impact assessment.

When a model suffers from large model uncertainties, the results of a parameter uncertainty analysis may be misleading. For instance, currently only information of the molecular weight and the amount of potentially produced acid of emitted substances and a reference substance are needed to compute acidification factors (HEIJUNGS et al., 1992). Parameter uncertainty in this case is negligible, but model uncertainty is certainly not, because fate of the substances and site-specific critical loads are not taken into account. The result of decreasing model uncertainty will in most cases be the implementation of more parameters in the computation of acidification factors, thereby increasing the importance of operationalising parameter uncertainty in the model.

4 Uncertainty due to Choices

When performing LCAs, choices are unavoidable. Examples of choices leading to uncertainty in the inventory analysis are the choice of the functional unit and the choice of the allocation procedure for multi-output processes, multi-waste processes and open-loop recycling. Furthermore, in some cases different characterisation methods can be used for the same impact category. Moreover, the weighting phase in LCAs is an area in which choices play a crucial role. Although many weighting methods have been suggested by LCA experts, only a few are operational and no general agreement exists as to which one should be preferred. For example, an authorised weighting set could potentially be based on political reduction targets, environmental control and damage costs and panel preferences in reducing environmental impacts (POWELL et al., 1997). The problem is even more complicated, because reduction targets are formulated at many policy levels and the panel preference may reflect the opinion of a societal group, of scientific experts, of governments or international bodies. Moreover, there is still some discussion about whether to use generic weighting sets or to perform weighting case-by-case for different product systems in LCAs (LINDEIJER, 1996).

The standardisation of procedures, such as the guidelines given by LINDFORS et al. (1995b) and ISO (1997a-d), is useful for reducing uncertainty due to choices to a broadly accepted level and stimulate unity in LCA practice. In addition, peer review can be used to judge choices on their merits. When standard procedures are not fully applicable, uncertainty due to choices may be made operational with the help of a scenario analysis, which can show the effect on LCA outcomes of several combinations of choices (LINDFORS et al., 1995a; KORTMAN et al., 1996). For instance, a scenario analysis can show differences in LCA outcomes due to the application of different allocation procedures, characterisation methods and weighting methods.

5 Spatial Variability

In LCA variability across locations, such as physico-chemical and ecological properties of the environment, background concentrations of chemicals and human population density, is generally not taken into account in LCA (HEIJUNGS et al., 1992; GUINÉE et al., 1996). In most LCAs all environmental interventions are summed up regardless of the spatial context of the intervention, introducing model uncertainty. A distinction between outdoor versus indoor emissions and emissions to land versus emissions to sea, for instance, could make the results of LCAs more appropriate (POTTING & BLOK, 1994). A way to address real world spatial variability is to distinguish compartments by choosing appropriate subregions for LCA purposes. Both inventory analysis and impact assessment have to be modified to incorporate the appropriate spatial variability for the interpretation of environmental interventions.

In LCAs the feasibility of dealing with spatial variability is limited. The first reason is that a detailed regional context of emissions is in some cases not known or irretrievable. For instance, only accumulated average environmental interventions associated with plastics, produced by European plants, are published (BOUSTEAD, 1993). Data of all the individual plants are not available and environmental interventions due to transport and the production of energy carriers, such as electricity, oil and gas have already been summed up with the process-specific interventions. As a

consequence, in these cases it is not possible to use spatially differentiated classification factors. Furthermore, detailed environmental information, such as physico-chemical properties, ecological properties and background concentrations is needed to compute site-dependent classification factors. Although this kind of information is available to compute country-specific acidification, eutrophication and photochemical ozone creation factors in Europe (POTTING et al., 1997), such detailed information may be lacking for other continents. In addition, detailed information relevant for other impact categories, such as human toxicity and ecotoxicity, may not be available.

6 Temporal Variability

Temporal variation is present in both the inventory and the impact assessment of LCAs. However, variations of environmental interventions over a relatively short time period, such as differences in industrial emissions on week days versus weekends or even short calamitous emissions, are not taken into account, because LCA emission data are commonly obtained by dividing yearly emission by yearly production. Temporal variability over the years may be made operational when inventory data of several years are collected (HANSSEN & ASBJØRNSEN, 1996). However, it will be very difficult to obtain yearly variations of environmental interventions for the entire life cycle. Furthermore, caution is needed in the interpretation of the yearly variations, because the variation could also be caused by unreliable or inaccurate measurements. In practice, it seems very hard to operationalise temporal variability in inventory data for the whole life cycle of a product system.

Not incorporating temporal variation in the inventory analysis also has consequences for the operationalisation of temporal variability in the impact assessment. Substance-independent variables, such as wind speed and temperature, are used for the computation of characterisation factors, such as toxicity potentials (GUINÉE et al., 1996). Although these variables obviously vary temporally, it is not possible to match the temporal variation of these variables with the inventory data, because temporal variation over short time periods is not made operational in the inventory analysis. Moreover, emissions of a certain substance, which often take place in different years for the several unit processes, have been summed up in the inventory. Instead of operationalising the temporal variability of these variables in the impact assessment, the mean (and uncertainty of the mean) for these parameters has to be estimated for the representative geographic region and time period.

A second type of temporal variability in the impact assessment, however, is operational. Global warming potentials (GWPs), ozone depletion potentials (ODPs) and photochemical ozone creation potentials (POCPs) differ, depending on the chosen time horizon to integrate potential effects (ALBRITTON et al., 1996; SOLOMON et al., 1995; ANDERSSON-SKÖLD et al., 1992). The temporal variability in these characterisation factors is caused by the difference in life times between the reference substance, chosen per impact category, and the remaining substances. This kind of temporal variability can be made operational by comparing model outcomes for several chosen time horizons, changing temporal variability in uncertainty due to choices. Characterisation factors computed for a short time horizon may serve as indicators for short-term effects, while longer time horizons may serve as indicators for longer-term effects.

7 Variability Between Sources and Objects

In both the inventory and the impact assessment, variability between sources and objects may influence LCA outcomes. Inherent differences in inputs and emissions of comparable processes in a product system, for example due to the use of different technologies in factories which produce the same material, cause variability in life cycle inventories (BOUSTEAD, 1993; HANSSEN & ASBJØRNSEN, 1996). Furthermore, variability between objects exist in the characterisation phase. For example, variability in human characteristics, such as body weight, consumption of food products and sensitivity for toxic substances, may cause variation in human toxicity potentials. Moreover, the weighting of environmental problems in the impact assessment could introduce variability between human preferences. When, for instance, the panel method is used to weight environmental problems, differences between individual preferences cause inherent variation in the final environmental indicator.

The effect on LCA outcomes of variability between sources and objects can be made operational by probabilistic simulation, analogous to the procedure for operationalising parameter uncertainty. Variability between objects should preferably always be taken into account in the impact assessment. The operationalisation in the inventory analysis, however, is dependent on the goal of the study. For example, if the goal is to improve the environmental profile of a product system, it could be informative to know the actual range of the environmental interventions in the inventory. Factories which produce the same product or material within one product system may have considerably different environmental interventions. When the output distribution of the environmental profile is analysed with a correlation analysis (→ *section* 2), it may become clear which data variability in the inventory mainly contributes to the range of environmental profiles. Consequently, a reduction of the sources which contribute to the upper tail of the data variability could be the main focus for product system optimisation. If, however, the goal of the study is to perform a product comparison, the average environmental profiles of the product systems is of particular interest. Consequently, variability between sources in the inventory should be transformed into the uncertainty of the mean. However, the representation of both variability between sources and uncertainty of the mean in probabilistic simulations is still interfered by measure-

ment inaccuracies. A quantitative example of how to deal with this complication is given in the Appendix.

8 Integration in LCA Research

Ideally, LCAs cover all the types of uncertainty and variability mentioned in the previous sections (→ *Table 1*), although for the inventory phase this may depend on the goal and scope of the analysis (→ *section 7*). In the near future, however, it will neither be possible nor feasible in product assessments to perform such a large-scale analysis. It seems at least feasible to deal with the following types of uncertainty and variability (→ *Table 2*): (1) parameter uncertainty and/or variability between objects and sources in the inventory analysis through the use of stochastic modelling, uncertainty/variability importance analysis or other techniques; (2) uncertainty due to choices in the inventory analysis, the choice of impact categories and the characterisation phase by means of standardisation, peer review and scenario analysis.

Operationalisation of parameter uncertainty and variability between objects and sources in the inventory phase, however, is most probably limited to the process data which are specific for the given product system under study, such as material use, energy use and process emissions. For widely used inventory data, such as the environmental interventions related to the production of electricity, heat and widely used

Table 1: Examples of types of uncertainty and variability related to the phase of LCA

Source \ Phase	Goal and scope	Inventory	Choice of impact categories	Classification	Characterisation	Weighting
Parameter uncertainty		Inaccurate emission measurements			Uncertainty in life times of substances	Inaccurate normalisation data
Model uncertainty		Linear instead of non-linear modelling	Impact categories are not known	Contribution to impact category is not known	Characterisation factors are not known	Weighting criteria are not operational
Uncertainty due to choices	Functional unit	Use of several allocation methods	Leaving out known impact categories		Using several characterisation methods within one category	Using several weighting methods
Temporal variability		Differences in yearly emission inventories			Change of temperature over time	Change of social preferences over time
Spatial variability		Regional differences in emission inventories			Regional differences in environmental sensitivity	Regional differences in distance to (political) targets
Variability between objects/ sources		Differences in emissions between factories which produce same product			Differences in human characteristics	Differences in individual preferences, when using panel method

Table 2: Overview of tools available to address types of uncertainty and variability in LCAs

Tools \ Types	Parameter uncertainty	Model uncertainty	Uncertainty due to choices	Spatial variability	Temporal variability	Variability in objects/sources
Probabilistic simulation	+					+
Correlation and regression analysis	+					+
Additional measurements	+					+
Scenario modelling			+		+	
Standardisation			+			
Expert judgement/peer review	+		+			+
Non-linear modelling		+				
Multi-media modelling		+		+		

bulk materials, like plastics, steel, aluminium, wood, etc., it is favourable to provide uncertainty estimates in general databases. However, in contrast to other environmental models, thousands of parameters are involved in the inventory analysis of product assessments, which make the feasibility of estimating underpinned uncertainty ranges for all these parameters in LCAs doubtful. Therefore, finding ways to simplify the uncertainty analysis in a systematic and transparent way is an important LCA research issue. Some possibilities to simplify the parameter uncertainty analysis are discussed in HUIJBREGTS (1998).

In addition to the above-mentioned analysis of uncertainty and variability in product assessments, other structural developments are necessary. The following developments focus on more general aspects in LCAs, such as (1) the reduction of model uncertainties in the inventory analysis through use of non-linear modelling, suggested by WRISBERG et al. (1997); (2) the reduction of model uncertainty in the characterisation phase, through use of multi-media modelling (GUINÉE et al., 1996; WEGENER SLEESWIJK & HEIJUNGS, 1996); (3) the operationalisation of parameter uncertainty and, if applicable, variability between objects in the environmental models which are used to compute characterisation factors; (4) the standardisation of the weighting procedure to guide uncertainty due to choices (LINDEIJER, 1996); and (5) the operationalisation of spatial variability in inventories and characterisation factors (POTTING et al., 1997). Co-operation with specialists of other scientific disciplines will facilitate the implementation of these improvement options. If widely accepted results of model improvements and uncertainty/variability estimates in characterisation factors are available, incorporation of these developments in product assessments will be possible.

Although dealing with uncertainty and variability is possible in product assessments, it remains unclear what the exact implications are for decision makers. Clear guidance needs to be developed how to take uncertainty and variability into account in decision-making processes. In this respect, special care is needed in the interpretation of model uncertainty. To some extent, it is not possible to reduce or operationalise model uncertainties, such as the lack of a detailed spatial and temporal differentiation in LCAs. Other environmental information, such as risk assessment results, may provide complementary information for decision makers. How to combine the results of the different methods also remains to be explored.

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Appendix: Combining measurement inaccuracies with either "variability between sources" or "uncertainty of the mean"

To calculate the distribution characteristics of the inventory data, the effects of measurement inaccuracies with either "variability between sources" or "uncertainty of the mean" should be combined. The implications are shown in a simplified example. It is assumed that the SO_2 process emissions of five factories, which produce the product P, are known (→ *Table 3*). Furthermore, it is assumed that the five factories are a representative sample of all product P producing factories, and that the emissions caused by these factories are described by a normal distribution. If inaccuracies in the measurement of SO_2 emissions are neglected, the variation in SO_2 emissions is represented by the standard deviation of the sample (SD_s), while the standard error of the mean (SEM_s) represents the uncertainty of the average SO_2 emission. Basic statistical rules can be applied to compute the SD_s and the SEM_s.

Of course, the exact SO_2 emissions of the five factories are not known precisely. The measurement inaccuracies are represented by the standard deviations per SO_2 emission (→ *Table 3*). If these inaccuracies are taken into account, the computation of the SD and the SEM changes. The $SD_{combined}$, which reflects both the variation between factories and the inaccuracy in measurements, is computed with the following equation:

$$SD_{combined} = \sqrt{\frac{1}{N}} = \left(\sum_{x=1}^{x=N} SD_x^2 + \sum_{x=1}^{x=N} SD_x^2 \right) \quad (1)$$

$SD_{combined}$ = Combined standard deviation of SO_2 emissions due to variation between factories and inaccuracy in measurements;
SD_s = Standard deviation of SO_2 emissions due to variation between the five factories;
SD_x = Standard deviation of SO_2 emissions due to inaccurate measurements in factory x;
x = Factory identification number;
N = Number of factories.

The $SEM_{combined}$ is computed by means of the following equation:

$$SEM_{combined} = \frac{SD_{combined}}{\sqrt{N}} \quad (2)$$

in which all variables equal those mentioned above, and the $SEM_{combined}$ represents the error of the mean SO_2 emission introduced by both the generalisation of the sample emission average to the emission average of all product P producing factories and inaccurate measurements. As can be seen in **Table 3**, the characteristics of the emission profile will change, depending on whether inaccuracy in combination with either variability ($SD_{combined}$) or uncertainty of the mean ($SEM_{combined}$) is taken into account.

Table 3: Characteristics of g SO_2 process emissions per kg product P

Emission	Factory A mean (sd)	Factory B mean (sd)	Factory C mean (sd)	Factory D mean (sd)	Factory E mean (sd)	Mean	SD_S	SEM_S	$SD_{combined}$	$SEM_{combined}$
g SO_2	16 (5)	20 (4)	18 (3)	25 (5)	30 (6)	21.8	5.7	2.5	7.4	3.3

Book Reviews

Environmental Life Cycle Analysis

Author: David F. Ciambrone
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This is a curious book. I usually start reading a book from behind and in this case found appendices, e.g. with recycling codes of plastics, an enumeration of several US- environmental laws (3 pages), an appendix C which contains only one table with dubious heat values (upper? lower?) and a section "References" containing 17 (!) citations, the most recent one from 1995 (a self-quotation), the others typically from around 1990. Only four of these quotations refer to LCA (early SETAC, Battelle and Franklin). The index does not show entries on "functional unit" nor on "global warming".
After this disappointing start, I was gratified by very reasonable ideas put forward in the introductory chapters, which explain the need for life cycle thinking and analysis (the term assessment is used alternatively). In a short historical section, a paper by Harold Smith (World Energy Conference 1963) is mentioned in which the cumulative energy concept was presented. LCA is correctly distinguished from the "fence line approach" (gate-to-gate).
The author, a former manager, is well aware about the environmental problems connected with production processes and other life cycle steps, and he also recognises the need for some kind of impact assessment which he mostly calls "MANPRINT", although no clear operationalism is given. The focus of the book is on inventory analysis of industrial production processes starting with design and including recycling and waste management. The different phases are described in detail and is this part which might also be of interest for an experienced practitioner as a kind of checklist. The author, who is aware of the fact that many ad hoc decisions have to be made, has requested transparency in all steps. The allocation problem is addressed for the case of coproducts. Nevertheless, no rule is given for open loop recycling.

The functionality as a basis for comparison is not really addressed; it is not clear, for instance, whether or not the different bags compared in the standard example (plastic vs. paper) are really functionally equivalent. Here, as well as in other cases, the text is not rigorous enough and does not represent the state of the international discussion (ISO is not even mentioned). There are also inconsistencies in the definition of the system boundaries (Fig. 3-1) where the usable products leave the system which is only true for coproducts.
There are sentences in this book which I like, e.g. "Don't forget to talk to the people actually doing the work". On the other hand, there are omissions and many errors. In a list of "life cycle participants", the practitioner is missing. The energy content of a paper bag is reported to be 1,340,000 MJ on two occasions. The units are a mixture of US and SI-units; 1 kWh is given (again) as 3.61 MJ: dear friends in the US please note that an hour has exactly 3600 seconds, not 3610 and that 1 J = 1 Ws, hence 1 kWh = 3.6 MJ. In the comparison between paper and PE bags there are several misleading and redundant statements. Data sources are described in a vague and general manner which is of little (if any) help for the practitioner, e.g. "Local, regional wastewater control agencies, the U.S. EPA or the U.S. Army Corps of Engineers may have data on discharges to natural watersheds such as streams, rivers, lakes, and ocean outfalls". These general statements are in no case followed by a quotation.
The general impression about this book is that it is based on an old manuscript (somewhere between 6 and 8 years), which has not been updated and, inevitably in this rapidly evolving field, cannot represent the state of the art. The basic ideas are correct, however, and it would be desirable that managers and politicians would have at least this basic knowledge about the product/environment interplay. For the expert, as stated above, the inventory part may contain some useful information. The book is certainly not suited for someone wishing to learn LCA from the beginning.

Walter Klöpffer
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